A Novel Approach to Partial Face Recognition: MKD-SRC

Mayank Mrinal[1], Hemam Julun Singh[2], Shubham U. Dudhe[3], Ketan R. Patil[4]
[1, 2, 3, 4] K.K. Wagh College of Engineering, Nashik

Abstract- *Face Recognition is defined as a methodology to check whether the captured image or input image is exactly similar to the predefined images present in the dataset. Day by Day there is arapid enhancement in the field of face recognition. Some of the different sorts of facial recognition techniques are finding faces in images with the controlled background, finding faces by color, finding faces by motion, finding faces in unconstrained scenes etc. Each and every approach has its own advantages and different way to perform. Thus, we are implementing a technique face recognition approach by using MKD-SRC Algorithm. The advantage of using this algorithm is that. We can apply it to partial or hidden faces also, even if the given input is partial or incomplete, then also we can use this method. Also, we can match the left part of the input left image with the right one in order to determine whether the image belongs to the same object or not. Compare the same with the FaceVACS and PittPatt, our algorithm provides the solution to general face recognition problem. Our technique will also be able to perform object categorization, in order to determine whether the object belongs to the same category or not.*

Keywords- MKD-SRC Algorithm, FaceVACS, PittPatt, keypoint descriptor, sparse representation and object categorization

I. INTRODUCTION

Over few decades, it had been excavated out that the Face Recognition technology has received a Substantial demand due to which lots of researches has been done on this area. Physical Science embarks that there is some specific part of human body which has its unique Identity like Eyes, Facial Parts, and Nose Structure etc. On account of these parameters, we can easily infer whether these objects are the part of given Human Body or Not. Thus, by using the technique of face recognition by using MKD-SRC Algorithm; which provide an approach through which we can compare partial face images with the image available in dataset of images in order to find Out whether the input images are associated with the part of available images. The benefit of this technique is that we Can compare partial input with the image available in dataset Partial Face Recognition, provides a solution to the under listed Questions: (i) Is it possible to recognize a person from a partial image of his face? , (ii) What size of the partial face and which portion of the face are critical for exact Face recognition? There is various application of Face recognition such as Information security and access control,

Law enforcement and private security, Electronics Surveillance system and more generally image understanding. The General approach of partial face recognition technique is based on Multi-Key point Descriptors (MKD) this technique does not require face alignment by eye coordinates or any other fiducial points. Invariant shape adaptation makes image matching more robust in reference with viewpoint changes which are desired in face recognition with pose variations. In Multi-Key Point Descriptor (MKD), the size of the descriptor of an image is determined based on actual content of the image. The MKDSRC framework that works for both holistic faces and partial faces can be sparsely represented by a huge dictionary which consists gallery of descriptors. Multitask sparse representation is inferred from an each probe face as well as Sparse Representation-based Classification(SRC) approach is applied for face recognition which is a fast atom filtering strategy for MKD-SRC to address large-scale face recognition (with 11,000 gallery images).

II. PROPOSED FRAMEWORK

In this paper, we are going to focus on the problem associated with the general formulation of the partial face recognition problem. Within the image, it does not require the presence of the eyes, nose, face alignment or any other facial component. In such a situation, we are not being aware about priori whether the input image of a face is partial or holistic. By using this idea, our goal is to give a general matching solution to attune all types of partial faces which are mentioned in Table 1.In Brief, this technique is based on a Multi Keypoint Descriptor (MKD) representation which can be used for the probe image as well as the gallery of the image which can be inferred as a dictionary. For each and every probe face, a Multitask sparse representation must be studied, and thus for face detection and Sparse Representation-based Classification (SRC) approach [7] is implemented. Therefore, this method is called as MKD-SRC. Fig. 2. Represents the flowchart of the proposed method: The uniqueness of the proposed technique involves:

1. A general partial face recognition technique without the requirement of face alignment, the MKD-SRC framework that works fine for both holistic faces as well as partial faces, and surpasses SRC [7] in order to address one sample-per-class problem.
2. A new key point descriptor is introduced, which is called the Gabor Ternary Pattern (GTP), whose function is to outperform the Scale Invariant Feature Transform (SIFT) [8] descriptor,
3. Finally, a fast atom filtering strategy for MKDSRC is applied in order to address a large-scale face recognition (with 10,000 gallery images).

Scenario	External occlusion	Self occlusion	Facial accessories	Limited field of view (FOV)	Extreme illumination	Sensor saturation
Examples	occlusion by other objects	non-frontal pose	hat, sunglasses, scarf, mask	partially out of camera's FOV	gloomy or highlighted facial area	underexposure or overexposure
Image						

TABLE 1: A CATEGORIZATION OF PARTIAL FACE IMAGE

This paper is based upon the preliminary work presented in [9]. The main differences are encapsulated as follows: 1) Method used in [9] make use of SIFT descriptor, instead of that, we propose a new keypoint descriptor (GTP) which outperforms.2) We will assist one-sample-per class problem in large-scale open-set identification setting for PFR, and it embarks that as compare to the FaceVACS and PittPatt, the proposed MKD-SRC method performs better, on the FRGCv2.0, AR, and Pub Fig databases. 3) And, for the purpose of partial face verification, we have extended the Scenarios, was proposed MKD-SRC method, which draws out better results on the LFW database.

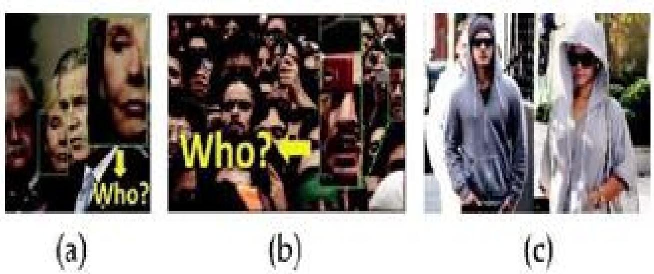

Fig. 1. Partial face examples. (a) Partial faces in the LFW Database [2]. (b) Partial faces in a crowd (c) Occluded faces

III. LITERATURE REVIEW

Some of the different face alignment techniques involve the Active Shape Model (ASM) [10] and the Active detect the two eyes and Appearance Model (AAM) [11], which depend on localizing and centering a specific fixed number (typically 68) of landmarks on theholistic face. In [12], a sparse representation-based alignment method under controlled by hooded sweatshirt and sunglasses (http://www.howtovanish.com/2010/01/avoidnosysurveillance-cameras/).

Nonfrontal face recognition has also attracted significant attention by multiview [19], [20] and cross-view [21], [22], [23], [24], [25], [26] face recognition. In the case of cross-view FR, most approaches apply 2D or 3D appearance models to synthesize face images in specific views. Multiview face recognition requires that the gallery contains a large number of poses for the corresponding subject that is not practically possible to satisfy in practice. In these approaches, a critical step is to localize a certain fixed number of representative facial landmarks and establish correspondences between two images in different views accordingly. Due to this, the images are expected to have visible anchor points irrespective of the view. Yang et al. [27] and Yi et al. [28] proposed an automatic partial face alignment and matching

Approach, for partial Faces obtained from a limited field of view. But, a technique for solving requires high-resolution images with the threshold value of interpupil distance 128 pixels with good skin texture, but it is should not impose to pose variations. Some FR approaches only partial face as an input, such as eye [29], nose [29], one-half (left or right portion) of the face [30], or the periocular region. Again, these methods require the presence of certain facial components and prealignment.

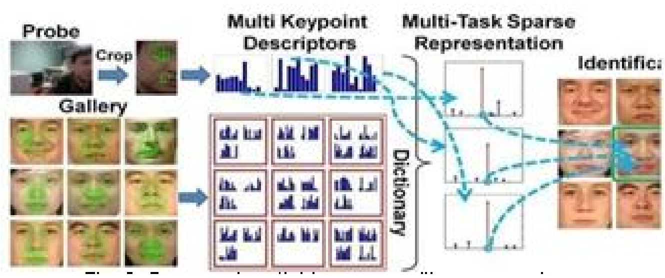

Fig. 2. Proposed partial face recognition approach

In comparison with the above SRC-based techniques, the proposed MKD-SRC technique uses a unique feature representation. To represent a face, since both SRC and LBPSRC needs aligned faces and use a single fixed-size feature vector (e.g., concatenated image pixels or LBP histograms), each column of their corresponding dictionary is associated with one gallery image. On opposite side, a partial face might be tedious to align and represent due to undisclosed missing facial regions, in such an intrigue. On the contrary, MKD-SRC makes use of variable-size description intended, in order to point out each face by a set of descriptors. As a whole, the MKD dictionary comprises of a huge number of gallery descriptors, making it possible, for a probe image in order to sparsely represent descriptors, irrespective of whether it represents a holistic or partial face. Thereafter, SRC requires an enough number of training samples which covers all possible illumination variations for each and every subject, which limits its application within certain boundaries. On the other hand, MKD-SRC performs satisfactorily where only one training sample per class is available. In the field of visual object categorization bag-of-words (BoW) representation is another representation that has been applied to face recognition. However, in the BoW representation, an assumption is made that the object image should not be significantly occluded; else, the descriptor histogram associated with thepartial image will be quite different from that of the original one.

Thus, the BoW representation proves to be insatiable for Partial Face Recognition (PFR).Numerous papers have been published on SIFT-based face recognition [1].But, all of them were imposed on prealigned face images. But the most significant and outstanding feature of SIFT matching is that it is frequent and it treats each pair image independently and that's why in the gallery set, it does not utilize acollaborative representation of different subjects. A number of local facial patches may appear to be similar to others, it is possible that, for an impostor pair, SIFT matching will find more matches than that of the genuine pair [9]. To alleviate this and to outrage a perfect result, the proposed MKD-SRC technique will perform keypoint matching via as parse representation of all gallery images in order to select the best match. Characteristics associated with MKD-SRC in comparison with the various existing framework are enfolded in Table 2. The rest part of paper is formulated as follows: If we come closer to Section 2, it shows well formulated alignment-free partial face representation method. For Section 3, an MKD-SRC algorithm implied by us. Extensive experiments are demonstrated in Section 4, shown in the table, and ultimately the whole framework has been clinched by us and its associated future work in Section 5.

IV. MKD-SRC ALGORITHM

According to Wright et al. [7] sparse linear combination of gallery images represents a probe image very effectively. Thus as a result, of this algorithm is called as SRC. Thus, in this paper, by using a large dictionary of keypoint descriptors, we have formulated to apply SRC in place of applying it directly to raw face image pixels; this acts as the key for the proposed alignment-free partial face recognition approach.

4.1 Gallery Dictionary Construction

The construction of gallery is as follows: Firstly, an MKD representation is developed for each image. Suppose k_c keypoints, say, pc1, pc2, ., p_{ckc} , are detected for class (subject) c in the gallery. Let us suppose that if an assumption is made that class c has multiple face images in the gallery, now we just incorporate the keypoints which are obtained from all of them. The corresponding k_c GTP descriptors are denoted by d_{c1}; d_{c2} . . . ; d_{ckc} , where each descriptor is an M-dimensional vector in our case, M = 128.

Let

$$Dc = (dc1, dc2, \ldots, d_{ckc}) \qquad (1)$$

This way the descriptors belonging from the same class leads to the formation of sub-dictionary of size M kc representing class c. A gallery dictionary for all the C classes is built as

$$D = (D1, D2, \ldots, DC) \qquad (2)$$

Note that D has a total of K $=\sum^{c}{}_{C-1}$ kc descriptors, resulting in an M * K dictionary. Typically, K is very large (e.g., over 1 million), which makes D an over complete description space of the C classes. Therefore, any descriptor from the C classes can be linearly represented in terms of the dictionary D. According to the theory of compressed sensing (CS), a sparse solution is possible for an overcomplete dictionary; therefore, we can express any descriptor from a probe image by a sparse linear combination of the dictionary D.

4.2 Multitask Sparse Representation For a probe face image with n descriptors in the given scenario:

$$Y = (y1, y2, \ldots; y_n) \qquad (3)$$

Subsequently, sparse representation problem is formulated as

$$X=\text{argmin} \sum_{i=1}^{n} ||x_i||_0, \text{ s.t. } Y = DX$$

Where $X = (x_1, x_2, \ldots, x_n) \in R^{k*n}$ is the sparse coefficient matrix, and ||.|| denotes the l_0 norm of a vector. Based on theresult from compressed sensing, sparse signals can be recovered with high probability via the l_1-minimization. Therefore, we solve the following l_1-minimization problem instead (3):

$$X = \arg\min \sum_{i=1}^{n} ||x_i||_1, \text{ s.t. } Y = DX \qquad (4)$$

This is a multitasking problem since both X and Y have multiple columns.

Inspired by Wright et al. [7], we adopt the following multitask SRC to determine the identity of the probe image:

$$\min r_c(Y) = \frac{1}{n}\sum_{i=1}^{n} ||y_i - D_c\delta_c(X_i)||_2^2 \quad (5)$$

Where $\boldsymbol{\delta}_c(.)$ is a function which selects only the coefficients corresponding to class c Equation (5) applies a sum fusion among reconstruction residuals of the n descriptors with respect to each class, and determines the identity based on the least residual. Therefore, an unknown partial face in the probe can be recognized by computing (4) and (5).

4.3 Fast Filtering

In practice, the size (K) of the dictionary D can be of the order of millions, making it difficult to solve (4). Therefore, we adopt a fast approximate solution. For each probe descriptor y_i, we first compute the following linear correlation coefficients between y_i and all the descriptors in the dictionary D:

$$Ci = D^T y_i,\ i = 1, 2, \ldots, n: \qquad (6)$$

Then, for each y_i, we keep only L (L << K) descriptors according to the top L largest values of C_i, resulting in a small sub-dictionary $D^{(i)}_{M*N}$. Next, D is replaced by $D^{(i)}$ in (4), and (5) is adjusted accordingly.

ALGORITHM

Algorithm 1. The MKD-SRC Algorithm

Input: As gallery images of C classes; probe image I; parameter L

Output: We get Identity C of the probe image I.

1. Enrollment: Initially, Extract multi-keypoint descriptors (GTP) from every gallery image then after this, build the Dictionary
   $D = (D1, D2, \ldots DC) \in RM * K$
2. Recognition:
3. Extract MKDs from the probe image:
   $Y = (y_1, y_2, \ldots, y_n) \in R^{M*n}$;
4. For i = 1 to n do
5. Compute top L descriptors from (6), resulting in a Sub dictionary $D^{(i)}_{M*N}$;
6. Solve (4) with D_M
7. end
8. Solve (5) to determine the identity c;

4.4 MKD-SRC for Partial Face Verification

Given a gallery set, the residual defined in (5) can be used as the dissimilarity score for face identification. However, the SRC algorithm was originally proposed for face identification purpose, the work which has been done so far for SRC-based face verification is not sufficient. Here, we propose a simple extension of the MKD-SRC algorithm for image identification. The Image Identification task is to determine whether a given pair of face images, say M and N, whether belong to the same subject or it has been belonging to another pair. Therefore, here we have used a normal set of background face images along with the image I as a virtual gallery set, and the other input face image J as the probe which gives a brief idea. It should be noted that even though the set of background face images does not hold the same set of anidea as either of the two input images, we will get the result. Finally, the MKD-SRC algorithm is filed to the set of image, for which the verification score is scored as 1 - rc, where rc is defined in (5) and c is the class for image I. In order to make the verification score a symmetric function of I and J, we must put J in the gallery set and u apply I as the probe, and the average score is computed which acts as the final score.

V. FUTURE WORK & CONCLUSION

Thus, we have presented the problem of face recognition from a partial patch of the image and presented an alignment-free approach referred as MKD-SRC. Our technique represents each face image with a set of keypoint descriptors (GTP and SIFT) and implements a huge class of dictionary from all the gallery descriptors. Thus, the dictionary can sparsely represent by descriptors of a partial probe image, and the identity of the probe can be referred accordingly. The proposed technique shows matching results on obtained partial faces, occluded holistic faces (AR database), and occluded or nonfrontal faces collected in unconstrained scenarios. A comparison with two commercial face matchers, FaceVACS, and PittPatt, shows that MKD-SRC, particularly with the face recognition problem. If in case a partial face cannot be detected, then our technique is still capable of matching score for given manually cropped face region. Thus, the general framework of MKD-SRC can be promising one in order to apply MKDSRC to other image areas, such as object categorization.

REFERENCES

[1] Shi, Yishu; Xu, Feng; Ge, Feng-Xiang;"SIFT-type descriptors for sparse-representation-based classification", International Conference on Natural Computation (ICNC), Vol. 10, Aug-2014.

[2] Shengcai Liao, Anil K. Jain, Fellow, IEEE, and Stan Z. Li "Partial Face Recognition:Alignment-Free Approach" IEEE Transactions On Pattern Analysis And Machine Intelligence, Vol. 35, No. 5, May 2013

[3] Renliang Weng, Jiwen Lu, Junlin Hu, Gao Yang, Yap-Peng Tan, Robust Feature Set Matching forPartial Face Recognition, IEEE International Conference on Computer Vision (ICCV), 2013.

[4] G. Hua, M.-H. Yang, E. Learned-Miller, Y. Ma, M. Turk, D.J. Kriegman, and T.S. Huang, "Introduction to the Special Section on Real-World Face Recognition," IEEE Trans. Pattern Analysis and Machine Intelligence, vol. 33, no. 10, pp. 1921-1924, Oct. 2011.

[5] G.B. Huang, M. Ramesh, T. Berg, and E. Learned-Miller, "Labeled Faces in the Wild: A Database for Studying Face Recognition in Unconstrained Environments," Technical Report 07-49, Univ. of Massachusetts, Amherst, http://vis-www.cs.umass.edu/lfw/, Oct. 2007.

[6] FaceVACS Software Developer Kit, Cognitec Systems GmbH, http://www.cognitec-systems.de, 2012.

[7] PittPatt Software Developer Kit, Pittsburgh Pattern Recognition, Inc., http://www.pittpatt.com, 2012.

[8] "Police Use Facial Recognition Technology to Nab Rioters," http://www.msnbc.msn.com/id/44110353/ns/technology_and_scienc e-tech_and_gadgets/#.TkR_lnO4KsJ, 2012.

[9] "Face Recognition Technology Fails to Find UK Rioters," http:// www.newscientist.com/article/mg21128266.000-facerecognitiontechnology-fails-to-find-uk-rioters.html, 2012.

[10] J. Wright, A.Y. Yang, A. Ganesh, S.S. Sastry, and Y. Ma, "Robust Face Recognition via Sparse Representation," IEEE Trans. Pattern Analysis and Machine Intelligence, vol. 31, no. 2, pp. 210-227, Feb. 2009.

[11] D.G. Lowe, "Distinctive Image Features from Scale-Invariant Keypoints," Int'l J. Computer Vision, vol. 60, pp. 91-110, 2004.

[12] S. Liao and A.K. Jain, "Partial Face Recognition: An Alignment-Free Approach," Proc. IAPR/IEEE Int'l Joint Conf. Biometrics, Oct. 2011.

[13] T.F. Cootes, C.J. Taylor, D. Cooper, and J. Graham, "Active Shape Models—Their Training and Application," Computer Vision and Image Understanding, vol. 61, no. 1, pp. 38-59, Jan. 1995.

[14] T. Cootes, G. Edwards, and C. Taylor, "Active Appearance Models," IEEE Trans. Pattern Analysis and Machine Intelligence, vol. 23, no. 6, pp. 681-685, June 2001.

[15] A.Wagner, J. Wright, A. Ganesh, Z. Zhou, H. Mobahi, and Y. Ma, "Toward a Practical Face Recognition System: Robust Alignment and Illumination by Sparse Representation," IEEE Trans. Pattern Analysis and Machine Intelligence, vol. 34, no. 2, pp. 372-386, Feb. 2012

[16] K. Hotta, "Robust Face Recognition under Partial Occlusion Based on Support Vector Machine with Local Gaussian Summation Kernel," Image and Vision Computing, vol. 26, no. 11, pp. 14901498, 2008.

[17] H. Jia and A. Martı´nez, "Support Vector Machines for Face Recognition with Occlusions," Proc. IEEE Conf. Computer Vision and Pattern Recognition, June 2009.

[18] H. Ekenel and R. Stiefelhagen, "Why Is Facial Occlusion a Challenging Problem?" Proc. IAPR/IEEE Int'l Conf. Bio-metrics, vol-3, 2009.

[19] D. Beymer, "Face Recognition under Varying Pose," Proc. IEEE Conf. Computer Vision and Pattern Recognition, pp. 756-761, June 1994.

[20] A. Pentland, B. Moghaddam, and T. Starner, "View-Based and Modular Eigenspaces for Face Recognition," Proc. IEEE Conf. Computer Vision and Pattern Recognition, pp. 84-91, 1994.

[21] T. Vetter and T. Poggio, "Linear Object Classes and Image Synthesis from a Single Example Image," IEEE Trans. Pattern Analysis and Machine Intelligence, vol. 19, no. 7, pp. 733-741, July 1997.

[22] D. Graham and N. Allison, "Face Recognition from Unfamiliar Views: Subspace Methods and Pose Dependency," Proc. Int'l Conf. Automatic Face and Gesture Recognition, vol. 3, pp. 348-353, 1998.

[23] Recognition by Elastic Bunch Graph Matching," IEEE Trans. Pattern Analysis and Machine Intelligence, vol. 19, no. 7, pp. 775-779, July 1997.

[24] V. Blanz, S. Romdhani, and T. Vett er, "Face Identification across Different Poses and Illumination with a 3D Morphable Model," Proc. Int'l Conf. Face and Gesture Recognition, vol. 3, 202-207, 2002.

[25] R. Gross, I. Matthews, and S. Baker, "Fisher Light-Fields for Face Recognition across Pose and Illumination," Proc. German Symp. Pattern Recognition, pp. 481-489, 2002.

[26] B.Heisele, P. Ho, J. Wu, and T. Poggio, "Face Recognition: Component-Based versus Global Approaches," Computer Vision and Image Understanding, vol. 91, nos. 1/2, pp. 6-21, 2003

[27] J. Yang, S. Liao, and S.Z. Li, "Automatic Partial Face Alignment in NIR Video Sequences," Proc. IAPR/IEEE Int'l Conf. Biometrics, vol. 3, 2009.

[28] D.Yi, S. Liao, Z. Lei, J. Sang, and S. Li, "Partial Face Matching between Near Infrared and Visual Images in MBGC Portal Challenge," Proc. IAPR/IEEE Int'l Conf. Biometrics, vol.3, 2009

[29] K. Sato, S. Shah, and J. Aggarwal, "Partial Face Recognition Using Radial Basis Function Networks," Proc. IEEE Int'l Conf. Automatic Face and Gesture Recognition, vol.3, pp. 288-293, 1998.

[30] S. Gutta, V. Philomin, and M. Trajkovic, "An Investigation into the Use of Partial-Faces for Face Recognition," Proc. Int'l Conf. Automatic Face and Gesture Recognition, pp. 33-38, 2002.

AUTHOR

Mayank Mrinal pursuing Bachelor degree in Computer Engineering from the University of Pune, India, with Machine Learning and BAI as his Interest. He is currently pursuing his career as a student At K.K Wagh College of Engineering Nashik, Maharashtra India. His research interests include computer Vision, pattern recognition, and machine learning, with a focus on image and video analysis, particularly face recognition.

Hemam Julun Singhis pursuing Bachelor degree in Computer Engineering from theUniversity of Pune, India as Pervasive Computing as his interest, He is currently pursuing his career as a student At K.K Wagh College of Engineering Nashik, Maharashtra India.

Shubham U. Dudhe ispursuing Bachelor degree in Computer Engineering from the University of Pune, India, with Pervasive computing as his interest, He is currently pursuing his career as a student At K.K Wagh College of Engineering, Nashik, Maharashtra India.

Ketan R. Patil ispursuing Bachelor degree in Computer Engineering from theUniversity of Pune, India with Machine learning as his interest, He is currently pursuing his career as a student At K.K Wagh college of Engineering, Nashik, Maharashtra India.